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# Analysis of Construction Trade Worker Body Motions Using a Wearable and Wireless Motion Sensor Network

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## Abstract

Biomechanical analysis of construction workers has been considerably improved with the development of wearable sensors. Information delivered by these systems is playing an important role in the evaluation of postures as well as in the reduction of work-related musculoskeletal disorders (WRMSDs). In this article, we present a novel system and data processing framework to deliver intuitive and understandable motion-related information about workers. The system uniquely integrates Inertial Measurement Unit (IMU) devices in a wireless body area network, and the data processing uses a robust state machine-based approach that assesses inadequate working postures based on standard positions defined by the International Organization for Standardization (ISO). The system and data processing framework are collectively validated through experiments carried out with college trainees conducting typical bricklaying tasks. The results illustrate the robustness of the system under demanding circumstances, and suggest its applicability in actual working environments outside the college.

*Keywords:* MSD, Postures, Construction, Wireless Sensor Network, IMU

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## 1. Introduction

Injuries and poor occupational health resulting from inadequate working conditions impact the wellbeing of the working population as well as countries' economies. Work-Related Musculoskeletal Disorders (WRMSDs)

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5 are injuries affecting muscles, joints and tendons, that result from repeated  
6 awkward postures and handling tasks, such as: forceful exertions in lifting or  
7 carrying loads, bending and twisting the back or limbs, exposure to vibration  
8 or repetitive movements.

9 In the construction sector, workers are particularly at risk of WRMSDs  
10 because of their high exposure to awkward postures, which are sometimes  
11 held for long periods of time, and also to carry heavy loads. According  
12 to Labour Force Survey and Reporting of Injuries, Diseases and Dangerous  
13 Occurrences Regulations (RIDDOR), in the period 2013-2016 in the UK, 64%  
14 of self-reported work-related illnesses were related to WRMSDs, resulting in  
15 1.2 million days off per year. Amongst construction trades, masonry and  
16 concrete workers appear the most at risk, with more than 110 cases per 10,000  
17 employees working full time [21]. Furthermore, carpet and tile installers are  
18 on their knees, crouching or stooping more than the 80% of the time, and  
19 bricklayers spend 93% of their time bending and twisting the body or doing  
20 repetitive motions [21].

21 These alarming statistics, along with economic and demographic pres-  
22 sures, have pushed the construction sector to consider occupational health  
23 as an increasingly important issue, worth the same amount of attention as  
24 safety. In a survey by the Constructing Better Health (CBH) Scheme, 97% of  
25 the respondents agreed or strongly agreed that health is taken more seriously  
26 than 10 years ago [5]. However, in a more recent study [7], 84% of respon-  
27 dents thought that more needs to be done to improve the implementation  
28 of occupational health in the industry, and 85% of them agreed that there  
29 is a need for industry-wide data to be analysed to spot health trends in the  
30 industry. When it comes to WRMSDs, one of the main issue is the lack of  
31 reliable and scalable approach to assess their risks.

32 In this paper, we present a new strategy and system to deliver intuitive  
33 and understandable motion-related information about workers in the con-  
34 struction. Accordingly, this paper is structured as follows. Section 2 reviews  
35 existing and recent initiatives by governments, companies and universities to  
36 develop different strategies to assess WRMSDs risks. In Section 3, we intro-  
37 duce our recently developed system to track the motion of workers, based on  
38 wearable Inertial Measurement Units (IMUs) connected through a wireless  
39 body area network; we call this system *Activity Tracking with Body Area*  
40 *Network (AT-BAN)*. In Section 4, we then present our novel algorithm to  
41 automatically recognise awkward postures in the collected IMU data. Sub-  
42 sequently, Section 5 reports experimental results on the assessment of brick-

43 laying tasks. Finally, Section 6 concludes the article and suggests future  
44 developments of the proposed system.

## 45 2. Background

46 The analysis of body motion has been tackled by experts during the last  
47 century for different purposes. Lillian and Frank Gilbreth were pioneers of  
48 motion study [6] in the field of industrial management. Focused on pro-  
49 ductivity and efficiency, they reduced all the hand motions carried out by  
50 workers in assembly tasks into some combinations of basic operations. They  
51 studied the basic operations (or ‘therbligs’) involved in tasks of bricklaying,  
52 reducing the number of required movements from 18 to 4.5 and increasing  
53 the number of laid bricks by 3 times [26].

54 Later on, various public agencies, companies and researchers have been  
55 involved in the creation of tools and techniques to reduce health and safety  
56 risks in the workplace, especially WRMSDs. Generally, they study the mo-  
57 tion of workers during their working day. Amongst the various guidelines,  
58 MAC [22] and ART [23] were developed by the British HSE for assessing  
59 manual handling and repetitive tasks. OWAS [13] was designed to modify  
60 the production line of a steel manufacturing company; and RULA [15] and  
61 REBA [14] for upper limbs and entire body assessment, respectively. Almost  
62 all these techniques are based on the visual analysis of the motion of workers  
63 by experts on ergonomics, who typically fill out a questionnaire or form to  
64 assess the performance [2]. Although these methods have proven to be some-  
65 what effective, they are neither objective nor precise, because they generally  
66 rely on some form of a subjective assessment of the assessor, which will likely  
67 to vary with experience and differ from one expert to another (subjectivity).

68 During the last decades, aiming to improve the repeatability of tests and  
69 deliver more accurate and precise results, numerous measuring devices have  
70 been proposed and investigated for biomechanical analysis in construction  
71 and other trades. Among those modern devices, marker-based optical motion  
72 tracking systems [8] have been widely used due to their precision. Trackers  
73 can be easily fit to the workers body, making systems wearable even in the  
74 jobsite during a working session. Another advantage of their wearability  
75 is that all body parts can be measured simultaneously, which enables more  
76 systematic evaluation of postures, something almost impossible for an expert  
77 at first sight. Alternatively, markerless optical motion tracking systems have  
78 been investigated using video cameras [11] or depth cameras [17]. These

79 systems have been also proved useful to conduct studies of postures and  
80 classify different movements. However, a major practical limitation of all  
81 these vision-based systems is that a direct line of sight is required to register  
82 the movements. In a similar manner, devices such as depth cameras, based on  
83 infrared projection systems, are too sensitive to varying lighting conditions  
84 and are not recommended for use outdoors. Their short range of operation  
85 as well as their narrow field of view are also limitations to be considered.

86 Recently, the miniaturisation of electromechanical systems has encour-  
87 aged the development of small wearable devices to register the movements of  
88 different parts of the body. These miniature devices integrate several sensors  
89 like accelerometers, magnetometers and gyroscopes in so-called IMUs. In  
90 addition to delivering results potentially as precise as optical systems, IMU  
91 systems are fully worn and so do not require any line of sight. Numerous  
92 works have been published in recent years on monitoring of movements of  
93 workers from different trades using IMUs. In 2014, Vanveerdeghem et al. [25]  
94 presented an IMU wearable system to control the motion of firefighters and  
95 detect if they are lying, walking or running. Rawashdeh et al. [16] used IMUs  
96 placed on the arms of athletes to help prevent injuries in overhead sports.  
97 In the field of construction, several researchers have developed IMU-based  
98 systems to study the behaviour of workers around the jobsite. Joshua and  
99 Varghese [12] proposed the use of IMUs data to classify workers activity as  
100 effective, ineffective or contributory. Very recently, Alwasel et al. [1] used a  
101 commercial wireless set of IMU sensors and the 3D SSPP software package  
102 <sup>1</sup> to estimate forces and moments performed by the major body joints of  
103 bricklaying trainees and workers. That work relates very much to the ap-  
104 proach presented in this paper, with similar conclusions drawn on the links  
105 between experience, productivity and ergonomic safety. Finally, Yan et al.  
106 [27] have developed a warning system for construction workers to prevent  
107 WRMSDs. They attach two wireless IMU sensors to the workers head and  
108 back to infer the angles described by head, neck and trunk. However, the  
109 scope of their setup is limited, since they do not consider the evaluation of  
110 limbs movement. Another approach is presented in [3, 4], in which the au-  
111 thors combine video with physiological status monitoring (PSM) technology  
112 and ultra wideband (UWB) to track the movements of workers and relate

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<sup>1</sup>Center for Ergonomics, University of Michigan, <https://c4e.engin.umich.edu/tools-services/3dsspp-software/>.

their physical characteristics to their position in the environment.

Selecting and employing internationally standardised rules by the International Organization for Standardization (ISO) is a first step towards a set of uniform criteria to evaluate body motions in the workplace and helps reduce the impact of WRMSDs [27]. For example, ISO 11228 [10] relates to the application of forces and loads handling, and ISO 11226 [9] is oriented to the acceptability of static working postures. Note that, although this paper is linked to tasks involving manual handling, its main objective is to study the postures of workers during their working day. For this reason, we focus on standard ISO 11228, which itself also refers to ISO 11226 for recommendations concerning working postures.

In the following, we present a new strategy to deliver intuitive and understandable motion-related information about workers in the construction field. Building on the approach initially presented in [24] and using the AT-BAN system, a scalable wireless body area network of IMUs developed by the research team, this novel approach evaluates the movement of several parts of the body and identifies postures of interest during bricklaying tasks, which subsequently provides information oriented to minimise the likelihood of WRMSDs. Unlike previous works [27], this system covers all the main limbs of workers and is able to register their activity over an entire day. Although the results presented in this paper correspond to the evaluation of the system for bricklaying tasks, the scalability of the system (both hardware and software) facilitates its use for different activities and trades.

### 3. Overview of the system

With the objective of recognising key postures and movements of workers, we have developed the Activity Tracking with Body Area Network (AT-BAN) system. This system has already been presented in previous works [20] [19], so we only briefly summarise it here.

Compact wearable IMU devices of dimensions 6 x 4 x 1.5cm are wirelessly connected to a work station, delivering a real-time, precisely synchronised and accurate stream of data, comprising: acceleration, magnetic heading and angular velocity, at a sampling rate up to 50 Hz. These sensors are attached to the subject's body by means of elastic straps, as shown in Figure 1(a), fitting tightly to the limbs, to prevent slippage, which could otherwise result in incorrect recognition of postures and movements. The number of sensors can vary, being adapted to the needs of the particular application.

149 The system used in the experiments reported here employs 8 sensors, and  
 150 can be operated continually for approximately 8 hours without the need for  
 151 a recharge. The 8 sensors are placed in the vulnerable parts of the body  
 152 associated with the bricklaying activity, i.e. upper/lower back, arms and  
 153 upper/lower legs [21]. This placement allows us to examine the back, shoulder  
 154 and knee activities in detail.



Figure 1: (a) Location of AT-BAN sensors on the body. (b) Set up of the system.

155 In addition to the data obtained from the sensors, working sessions were  
 156 recorded with a video camera (see Figure 1(b)). The acquisition of visual in-  
 157 formation has two purposes: (1) providing a visual reference point to evaluate  
 158 the performance of the algorithm developed for postures identification; (2)  
 159 evaluating the quantity of work carried out (e.g. number of bricks laid down  
 160 over a specific period), so that health performance can be gauged against  
 161 productivity. It must be highlighted that the video is not used anywhere in  
 162 the quantification of the body motions.

163 The subsequent data processing technique, the main contribution re-  
 164 ported in this paper, is described in Section 4.

## 165 4. Analysis of postures

### 166 4.1. State Machine

167 Every task performed by humans involves multiple body parts moving  
 168 in synchronization. Therefore, assessing the movement of a person requires

169 monitoring various body parts simultaneously. The accuracy and objectivity  
 170 of current evaluation methods have been improved with the use of sensors  
 171 attached to the body aiming to acquire data related to movement. However,  
 172 data obtained from such sensors is a set of continuous/analog signals that  
 173 can be displayed at best as a set of curves (see Figure 2(a)) that need to  
 174 be simultaneously analysed and interpreted. Such interpretation is complex,  
 175 even for professionals.

176 Thus, the first aim of this approach is to discretise the angular values  
 177 calculated after the data obtained from the sensors. For each instant of time,  
 178 analog angular values are converted to discrete data following the principles  
 179 of a finite-state: each sensor output will take a state depending on its present  
 180 and past states. As illustrated in Figure 2(b), more understandable plots are  
 181 delivered after processing the information.

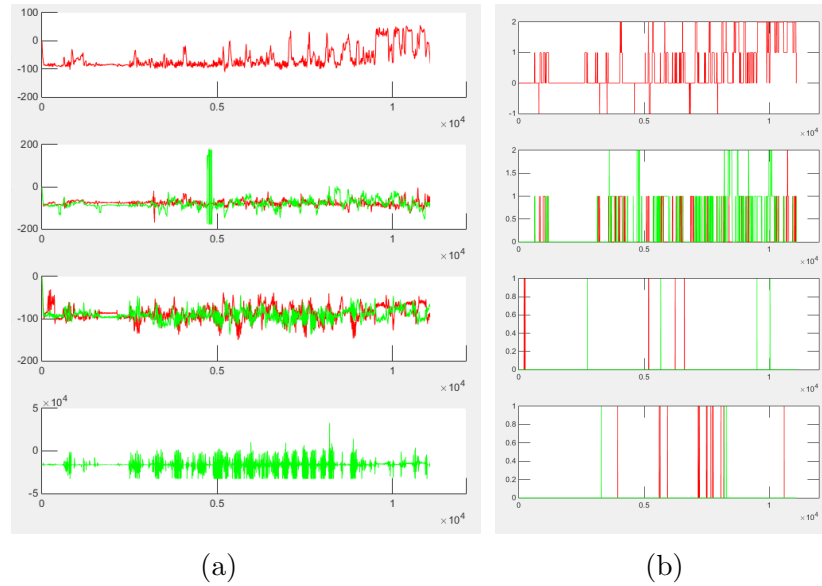


Figure 2: Angles of several sensors attached to the body of a worker during bricklaying tasks. (a) Continuous signal. (b) Discrete signal. From top to bottom: back, arms and upper legs (red for right limbs and green for left ones)

182 Depending on the rotation of one or several body joints with respect to  
 183 an initial orthostatic position (i.e. standing), each body part is assigned a  
 184 state. For example, considering the flexion of an arm, this can be ‘slightly  
 185 elevated’, ‘elevated’ or ‘too elevated’. However, these are fuzzy terms that  
 186 need to be defined by certain thresholds to provide an objective assessment.



187 Instead, we use angular thresholds specified in the standard ISO 11226 (see  
 188 Section 2). Amongst the postures evaluated in that standard, our study more  
 189 specifically focuses on (Figure 3): trunk inclination, knee flexion, kneeling,  
 190 and upper arm elevation, that are all determined by an angle. Note that these  
 191 motions are related to the joints most affected by WRMSDs as mentioned, as  
 192 discussed in Section 3. The angular thresholds corresponding to those joints  
 193 are summarised in Table 1.

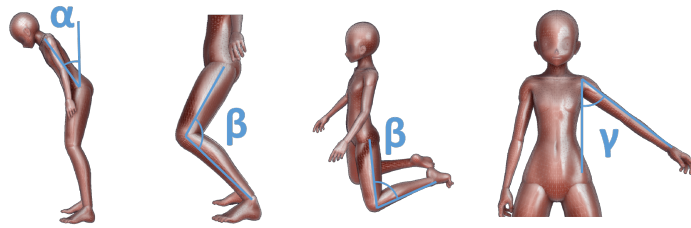


Figure 3: Basic movements and representative angle

194 These three different angles are measured by the AT-BAN system at  
 195 50Hz, and raw values are filtered using a median filter. The angular values  
 196 are then compared with a reference value, set from the initial standing-up  
 197 posture of the worker, to establish each individual joint state, as shown on  
 198 Table 1. To respond to sensor signal noise, we accept a change in the state  
 199 machine of a primary body position only if it is held for at least one second.  
 200 This approach is similar in effect to a Schmitt trigger [18]. The result of this  
 201 state evaluation process is illustrated in Figure 4, where angles and state  
 202 machine values are noted for a sensor attached to the upper back. Note that  
 203 values for  $\alpha$  are calculated as the difference between the angles plotted in the  
 204 graph and the reference initial value for that variable, which is around  $90^\circ$   
 205 in this particular case.

206 Following the idea of Gilbreth, this study interprets each task or activity  
 207 as a combination of simple movements performed by several body parts. For  
 208 example, the WRMSD risks associated to a task of spreading mortar on a row  
 209 of bricks can be seen as a mainly involving and combining trunk inclination  
 210 (back bending), knee flexion (squatting) and upper arm elevation. Therefore,  
 211 all the primary position states described in Table 1 are combined to infer  
 212 higher-level body postures, such as the twelve postures shown in Figure 5.  
 213 Table 2 illustrates how some higher-level postures are inferred from primary  
 214 position states.

Primary body part position	State	Angle	Definition
Trunk inclination	-1	$\alpha < 0^\circ$	Trunk backward inclination. Not recommended position
	0	$0^\circ \leq \alpha < 20^\circ$	Acceptable trunk inclination
	1	$20^\circ \leq \alpha < 60^\circ$	Trunk forward inclination. The holding time is evaluated according $t > -0.075\alpha + 5.5$ where $t$ is time in minutes and $\alpha$ is angle in degrees. If inequality is true, not recommended
	2	$\alpha \geq 60^\circ$	Trunk backward inclination. Not recommended position
Knee flexion	0	$\beta > 140^\circ$	Acceptable knee flexion
	1	$90^\circ < \beta \leq 140^\circ$	Extreme knee flexion. Not recommended position
Kneeling	0	$\beta > 90^\circ$	See knee flexion
	1	$\beta \leq 90^\circ$ (and calf parallel to floor)	Just one leg kneeling. Squatting movement considered
	2	$\beta \leq 90^\circ$ (and calf parallel to floor)	Kneeling
Arm elevation	0	$0^\circ \leq \gamma < 20^\circ$	Acceptable upper arm elevation
	1	$20^\circ \leq \gamma < 60^\circ$	The holding time is evaluated according $t > -0.05\gamma + 4$ . If inequality is true, not recommended
	2	$\gamma \geq 60^\circ$	Not recommended position

Table 1: Static primary positions according to ISO 11226 standard

#### 215 4.2. Performance Assessment Metrics/Scores

216 Results obtained during the joint angle and posture state classification  
217 stages are complex to interpret overall because of the amount of information  
218 that is generated. As a result, we defined Performance Assessment Metrics, or  
219 Scoring system, that summarises detailed joint and posture state information  
220 in one overall *Posture score* (or *MSD Risk Score*),  $S_{pos}$ . Furthermore, we  
221 define a *Productivity Score*,  $S_p$ , so that posture/WRMSD performance can  
222 be interpreted more objectively in light of the actual work performed by the  
223 worker. Indeed, assessing health and safety performance (here MSD) really

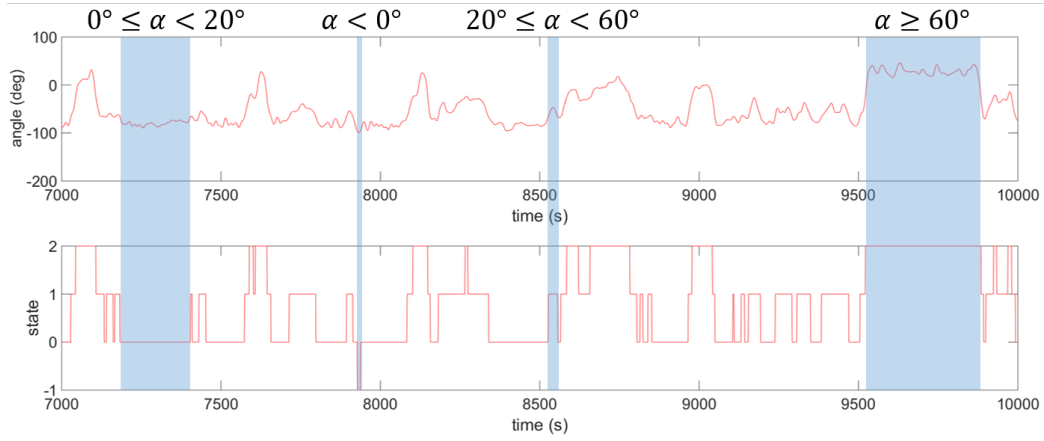


Figure 4: Angles and states of an upper back sensor. Some segments for different states are highlighted

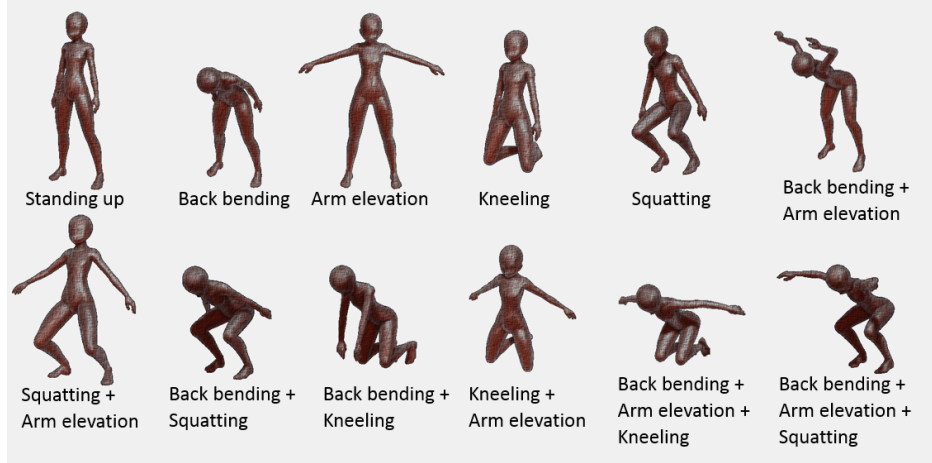


Figure 5: Identified postures

only makes in comparison with productivity. Taking the extreme case of a worker doing nothing but simply standing for 30min, they would have a great posture/MSD score; but clearly this great score should be contrasted with the total lack of work performed. The *Productivity Score* and *Posture Score* are easily presented to and therefore understandable by users and stakeholders.

For the *Productivity Score*  $S_p$ , we simply count the number of bricks laid down by the worker in visualising the video (this can be done rapidly by looking at the start and end state of the built wall at the beginning and end

	Trunk Inclination	Knee Flexion	Kneeling	Upper Arm Elevation
Back bending + Squatting	2	1	0	0
Squatting + Arm elevation	0	1	0	1
Back bending + Kneeling	2	0	2	0

Table 2: Inferring posture states (Figure 5) from primary position states (Table 1).

of the video, respectively). Equation 1 is then used to calculate  $S_p$ . In this equation,  $n_b$  is the number of bricks per minute laid down by the worker,  $c_b$  is an adjustment factor that considers the weight of the bricks (or blocks) and the number of items laid down by an average worker, and  $c_c$  is a *functional* efficiency factor that reflects the complexity of the wall (e.g. fine works, facing bricks, common bricks, ...).  $S_p$  increases with productivity.

$$S_p = n_b c_b c_c \quad (1)$$

The *Posture Score*  $S_{pos}$  is calculated as a weighted average of the state machines for all measured body part positions, i.e. all sensors, as summarised in Equation 2 where:  $|k_{ij}|$  is the absolute value of the state machine for the joint angle (i.e. sensor)  $i$  during the interval  $j$ ;  $\bar{\alpha}_{ij}$  (or alternatively  $\bar{\beta}_{ij}$  or  $\bar{\gamma}_{ij}$ ) is the mean value of the joint angle  $\alpha_i$  during the interval  $j$ ; and  $t_{ij}$  is the duration of the interval  $j$  for the joint  $i$ .  $S_{pos}$  theoretically increases with the risk of developing MSDs.

$$S_{pos} = \frac{\sum_{i=1}^m \left( \sum_{j=1}^{n_i} |k_{ij}| \bar{\alpha}_{ij} t_{ij} \right)}{\sum_{i=1}^m \left( \sum_{j=1}^{n_i} t_{ij} \right)} \quad (2)$$

## 5. Experiments

Aiming to validate the proposed AT-BAN system and the new posture detection algorithm, experiments have been conducted at Forth Valley College (FVC), a Scottish further education college. The set of experiments presented in this paper focused on bricklaying apprentices, the construction

trade considered to have the highest exposure to body bending/twisting and repetitive motions [21]. In this section, detailed information about data acquisition and analysis is provided.

### 5.1. Data Acquisition

Six male 1<sup>st</sup> and 2<sup>nd</sup> year persons, aged 16-34, between 1.70 and 1.95m tall and not seriously injured in the last year, participated in the trials. All were equipped with a set of 8 AT-BAN sensors, as shown in Figure 1. The test subjects performed routine tasks such as: carrying and spreading mortar and moving and lying different kind of bricks (20 and 14 kg blocks and standard 2kg bricks) in the college workshops, replicating real working environments and using standard tools and materials. Their movements were recorded for 20-minute sessions.

Together with the sensor data, synchronised video streams were also recorded. These are used to establish visual ground truth to qualitatively assess the performance of the proposed algorithms and to produce easily understandable results for the users of the system. Furthermore, the videos are used to extract the amount of work achieved during the recorded sessions, so as to obtain some productivity performance information and score.

### 5.2. Data Analysis

The generation of a ground truth model to evaluate the proposed system would not be a trivial task at all. Even with video recordings and expert assessment – i.e. current best practice – a reliable identification of postures (e.g. as defined by ISO standards) would be hard to achieve. In fact, this method can be argued to be even less reliable than our proposed system. Using an optical tracking system would probably be the ideal approach to obtain comparative ground truth information for the individual angles. But, the equipment could not be obtained and installed in the college lab where the experiments were conducted. Furthermore, those systems are not perfect either and may not have worked well with the workers wearing their typical working outfits and PPE. As a result, we must rely for now on a qualitative analysis of the performance of our system by comparing the automatically detected motions with those visible in the synchronised video. For example, we refer the reader to one of the sessions results in the videos attached to

283 this manuscript <sup>2</sup> <sup>3</sup>. As can be seen, all the steady primary position states  
284 are properly identified. A short delay in the detections can be observed  
285 during noticeable changes in the posture. This happens because of the time  
286 threshold we employ to accept changes in primary body positions (see Section  
287 4.1). This may arguably lead to some false negative posture detections when  
288 postures are held only for very short periods (such cases are visible a few times  
289 in the videos). But, the time threshold also helped smooth measurement  
290 errors or spikes and therefore prevent other detection errors.

291 Remarkable information related to both posture and productivity can be  
292 extracted from the performed trials. Table 3 summarises descriptive param-  
293 eters along with productivity and posture obtained for the 6 test subjects.  
294 While the number of bricks handled in each experiment is not very large, the  
295 productivity achieved by the test subjects clearly reflects experience gained  
296 over time, with the test subjects with more than 12 months of experience  
297 showing similar productivity to that of professionals, that can lay between 15  
298 and 20 20kg-concrete blocks per hour (20 to 30 in the case of 14kg blocks).

299 Regarding productivity, the results indicate that the more experienced  
300 test subjects spend less time per brick in postures not recommended by the  
301 ISO 11226 standard. Furthermore, it can be observed how test subjects tend  
302 to bend their backs, aiming to increase productivity, instead of approaching  
303 blocks with more favourable postures (i.e. squatting). If we extrapolate  
304 the observed back bending times to a complete working day, even if we do  
305 not consider some factors affecting workers' performance, such as fatigue  
306 or recovery time, we find that the persons would cumulatively spend in this  
307 detrimental posture durations ranging between 4.5 and 7 hours. These habits  
308 will most likely entail back problems and days away from work in the future.

309 The graphs in Figure 6 show the *productivity* and *posture* scores obtained  
310 for the 6 test subjects. While productivity scores increase with experience,  
311 it is interesting to note how posture scores do not show such a correlation.  
312 Note that the recently published work of Alwasel et al. [1] reaches similar  
313 conclusions. This small or even lack of improvement in posture scores over  
314 time is interesting in light of the steady improvement in productivity, which  
315 could be attributed to insufficient training about harmful postures and best  
316 practices.

---

<sup>2</sup><http://bit.ly/7C-FVC>

<sup>3</sup><http://bit.ly/82-FVC>

<b>Test subjects</b>	<b>1</b>	<b>2</b>	<b>3</b>	<b>4</b>	<b>5</b>	<b>6</b>
Experience (months)	30	24	3	3	18	18
Trial duration (min)	20	20	20	20	20	20
Brick weight (kg)	20	20	2	2	14	14
Number of handled bricks	11	12	7	5	6	8
Effective time per brick (s)	82	85	180	240	160	120
Bending time per brick (s)	79	84	151	141	159	119
Kneeling time per brick (s)	0	0	0	85	0	0
Squatting time per brick (s)	0	8	0	17	33	3
Arm elevation time per brick (s)	3	2	87	45	7	8

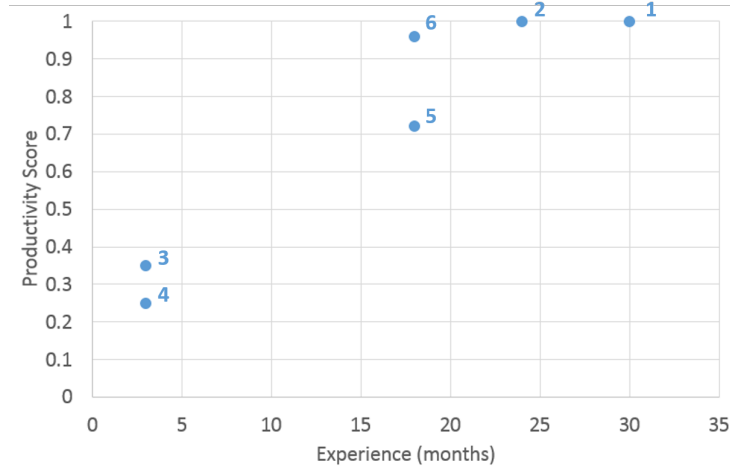
Table 3: Descriptive parameters along with productivity and posture metrics obtained for the 6 test subjects during bricklaying activities.

### 5.3. Data Visualisation

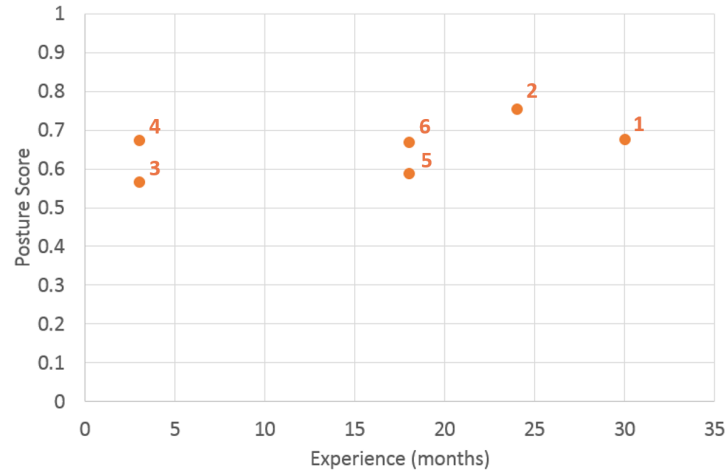
As illustrated in Figure 7 and the two videos attached to this manuscript, two different types of visual outputs have been developed to ease the review of the results by non-technical experts.

The first visual output is a video, showing the higher-level posture detections over time in synchronisation with the captured video stream. A red line moves along the coloured bars, showing the progress of the activity and indicating the identified primary positions. On the right-hand side, a mannequin is used to report the high-level posture detections in real-time. The comparison of this mannequin with the true posture of the worker visible in the video has shown to be valuable not only to our internal validation of the AT-BANs performance, but also to demonstrate its performance to project partners like the staff of the college. It is important to highlight that this visual output is only available for cases when video recording is used, i.e. for stakeholder engagement. In general contexts (e.g. on a real construction site with the worker moving locations during an entire day), video recording would not be feasible, so that this output would not be produced.

The second output summarises the results obtained over the recorded session, delivering information about the number of detections of and time spent in each primary positions during the studied session. In contrast with the first visual output, this second one is obtained from the processed IMU data only, and so is provided when using the system in any context (e.g. on a real construction site with the worker moving locations during an entire



(a) Productivity scores.



(b) Posture/MSD scores.

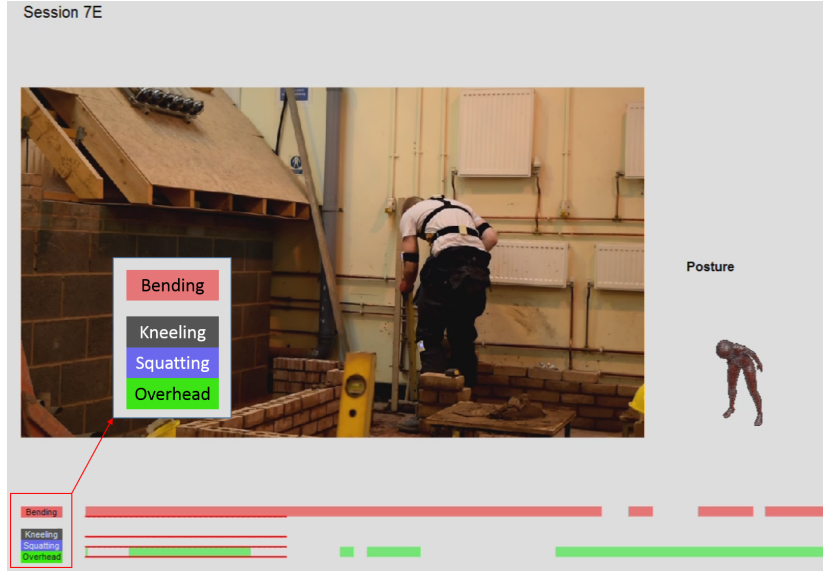
Figure 6: Productivity scores (a) and Posture (or MSD risk) scores (b) for the 6 test subjects. The numbers refer to each person ID in Table 3.

340 day).

## 341 6. Conclusions

342 The continuous assessment of workers body motion in the working envi-  
 343 ronment can help identify and mitigate the risks of WRMSDs and improve  
 344 their wellbeing. Although governments, public bodies and researchers have





(a) Frame of the video enriched with the identified motions.



(b) Left: Timeline of a trial session with identified motions. Right: Percentage of time assigned to each primary position.

Figure 7: Visual outputs presenting the session results to non-technical users like trainees and staff of the college.

345 developed methods to evaluate the movements of workers and correct their  
 346 movements toward a healthier performance, most of them are based on visual  
 347 observations and hardly depend on the experience of the assessor.

348 A novel and more automated approach is presented in this paper to iden-  
 349 tify detrimental postures in construction jobsites. This method, based on  
 350 the use of a wearable wireless network of IMU devices, the AT-BAN system,  
 351 discriminates between basic postures and identify those that are prone to  
 352 increase the risk of WRMSDs, according to existing ISO standards.

353 Angular values used as reference for this work have been extracted from

354 the standard ISO 11226, which contains a collection of tables, diagrams and  
355 equations to determine the acceptability of static working postures. Even  
356 if there exists a standard devoted to dynamic activities (ISO 11228), rules  
357 detailed in that document are oriented towards parameters indirectly related  
358 to ergonomics and postures, such as loads or repetitions. This highlights a  
359 gap in standards available for analysing dynamic activities, which is in fact  
360 likely due to the impossibility to establish standards without adequate and  
361 stable technologies that can capture data with the required accuracy. The  
362 system presented in this paper is intended to push the boundaries further,  
363 to eventually enable the development of such standards.

364 To test and validate the proposed tool, several working sessions were  
365 recorded with actual trainees in a local college. Results show that harmful  
366 postures can be detected, and suggest that, while productivity performance  
367 seems to improve with experience (as expected), our posture score suggests  
368 no improvement with experience. However, these results were only obtained  
369 with 6 test subjects and more trials, involving a larger population and con-  
370 sidering both novice and experts workers both in the college and on site, need  
371 to be performed in order to confirm those results and the general usability  
372 of our system.

373 Future works will consider the use of loads for analysis of dynamic pos-  
374 tures, and the use of the system will be investigated for other construction  
375 trades (e.g. painting and decorating). We will also look into integrating  
376 sensors to tools to monitor a wider range of activities and health issues (e.g.  
377 vibrations). Finally, through more trials, we should be able to develop a  
378 dataset large enough to investigate machine learning algorithms to more po-  
379 tentially more robustly identify postures and motions.

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